# Analysing the Impact of ENERGY STAR Rebate Policies in the US *

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**Abstract**

In this paper we estimate the impact of rebate policies in various US states on the sales share of ENERGY STAR household appliances. We use annual ENERGY STAR sales data for clothes washers, dishwashers, refrigerators and air conditioners from 2001 to 2006 and the variation in the coverage of rebates across US states and over time to identify the impact of rebate policies. We use, at first, a difference-in-differences approach to estimate this impact. Then, we take into account the possibility of rebate policies being endogenous and use an instrumental variables approach in a fixed effects panel data regression model. Results suggest that rebate policies increase the sales share of ENERGY STAR household appliances by around 3.3 to 6.6 percentage points and this represents an impact of around 9% to 18% on the mean level of the sales share of ENERGY STAR household appliances in the US between 2001 and 2006. We conclude that our estimates indicate that rebates on ENERGY STAR appliances increase the uptake of energy-efficient appliances.

**Keywords:** Residential appliances; ENERGY STAR; Rebate policies; Difference-in-differences; Non-linear methods.

**JEL Classification Codes:** C13, C33, C36, L68, L94, Q4.

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# 1 Introduction

The global carbon dioxide ($CO_2$) emissions from the consumption of energy was a little over 32,300 million metric tonnes in 2012 of which the United States contributed around 16% (Energy Information Administration, 2015a). About 38% of the total U.S. energy-related $CO_2$ emissions in 2014 were by the electric power sector (Energy Information Administration, 2015b). While the per capita $CO_2$ emissions from the consumption of electricity in the US remains one of the highest in the world, chiefly due to its reliance on coal-fired power plants, there have been several policy initiatives undertaken at the state and federal levels to reduce these emissions. These initiatives include the implementation of appliance standards, financial incentives in the shape of cash rebates, income tax credits and deductions, and the introduction of information and voluntary programmes like Climate Challenge and ENERGY STAR. These energy efficiency policies have been promoted to also reduce air pollution from pollutants such as sulphur dioxide, nitrogen oxides, ozone and particulate matter, to improve energy security and to prevent the need for constructing increasingly expensive new power plants. The World Energy Outlook 2009 (International Energy Agency, 2009) and several other studies (Creyts et al., 2007; Granade et al., 2009; Nauclér and Enkvist, 2009) highlight the huge potential of $CO_2$ reductions from increased end-use energy efficiency. In view of these advantages of energy efficiency, policy instruments that promote the increase in energy efficiency of electrical appliances like household appliances play an important role.

The voluntary eco-labelling programme, ENERGY STAR, was introduced in 1992 by the United States Environmental Protection Agency (EPA). It was designed to promote the use of energy-efficient products and thus help to reduce the emissions of greenhouse gases by consuming less electricity. Appliances with the ENERGY STAR label usually consume about 20 to 30 percent less energy than required by federal standards (Tugend, 2008).[1] The Climate Challenge was launched in 1993 and was a voluntary partnership between the US Department of Energy (DOE) and national utility trade associations to reduce greenhouse gas emissions. Participants in the programme are encouraged to make commitments to reduce carbon emissions. In this paper, we will focus on the ENERGY STAR programme and, specifically, the ENERGY STAR programme for clothes washers, dishwashers, refrigerators and air conditioners.

Federal and local governments and utility companies across the US promote the adoption of ENERGY STAR-labelled products by offering financial incentives, usually in the form of mail-in rebates. These are offered to customers who fill in the rebate form and return it to the respective entity offering the rebate. These financial incentives are offered by utilities in certain states as part of the Energy Efficiency Resource

[1] For a more comprehensive description of the ENERGY STAR programme please refer to Brown et al. (2002) and McWhinney et al. (2005).

Standard (EERS) programme that require energy efficiency programmes to be implemented. The adoption of energy-efficient appliances has public benefits, through reduced GHG emissions, as well as private benefits, through savings in utility bills. According to estimates by the EPA, the ENERGY STAR programme has led to energy and cost savings in the US of about $18 billion in 2010.[2] Howarth et al. (2000) state that improvements in energy efficiency in the Green Lights and ENERGY STAR Office Products programmes should lead to reductions in energy use with no significant "rebound effect".[3] Webber et al. (2000) conclude that 740 petajoules[4] of energy has been saved and 13 million metric tons of carbon avoided due to the ENERGY STAR programme. In a more recent study using a bottom-up approach, Sanchez et al. (2008) estimate that ENERGY STAR-labelled products have saved 4.8EJ[5] of primary energy and avoided 82Tg C equivalent. Given the importance of the ENERGY STAR programme to the EPA and the US Department of Energy[6] and the high visibility of ENERGY STAR-labelled products, with public awareness of the label increasing from 56% in 2003 (U.S. Department of Energy, 2004) to more than 80% in 2011[7], it is important to evaluate the impact of financial incentives provided by utility companies designed to promote the sales of ENERGY STAR household appliances. It is also important to note that financial incentives to promote the adoption of ENERGY STAR appliances are not present in all US states. We use this variation in financial incentives to analyse the impact of these policy instruments.

In this paper we focus on rebate policies which are, in general, part of a wider array of programmes labelled demand-side management (DSM) programmes. DSM programmes undertaken by utility companies refer to the "planning, implementation, and monitoring of utility activities designed to encourage consumers to modify patterns of electricity usage, including the timing and level of electricity demand" (Energy Information Administration, 2009). Initiated primarily to combat rising gas and oil prices in the late 1970s these initiatives have increased from 1.4 billion dollars in 1999 to 4.2 billion dollars in 2010 (Energy Information Administration, 2011) after a dramatic fall in DSM spending in the mid to late 90s due to restructuring of electricity markets.[8] There was uncertainty about the restructuring efforts and ability to recover spending

[2] http://www.energystar.gov/index.cfm?c=about.ab_history, website accessed 17 April, 2012

[3] The "rebound effect" is a phenomenon, described by Khazzoom (1980), whereby electricity consumption increases due to an increase in energy efficiency. It is caused by the fact that an increase in the level of energy efficiency leads to a decrease in the price of energy services and, via a substitution effect, an increase in demand for these energy services. This, subsequently, causes an increase in the demand for electricity. This rebound effect is referred to as the direct rebound effect. Indirect rebound effect leads to the energy saving being off-set by more energy usage in another activity. The literature on the rebound effect provides no consensus on the degree of rebound observed. While there are numerous studies, the interested reader may refer to volume 28 of *Energy Policy* in June 2000 for a more detailed discussion of the rebound effect. For more recent discussions of the rebound effect please refer to, for example, Van den Bergh (2011), Turner (2013), Gillingham et al. (2015), Borenstein (2015) and Saunders (2015).

[4] 1 petajoule = $10^{15}$ Joules. 740 petajoules is equivalent to $205.5 \times 10^6$ MWh. 1 MWh = $3.6 \times 10^9$ Joules.

[5] 1EJ (Exajoule)=$10^{18}$ Joules. 4.8EJ is equivalent to $1.3 \times 10^9$ MWh. 1Tg (Teragram) = $10^{12}$ grams

[6] The ENERGY STAR programme has been jointly administered by the EPA and the US Department of Energy (DOE) since 1996.

[7] http://www.energystar.gov/index.cfm?c=about.ab_milestones, website accessed 21 August, 2012

[8] See Eto (1996), Nadel and Geller (1996) and Nadel (2000) for a history of utility DSM programmes in the US.

on energy efficiency through cost recovery mechanisms. As a result, DSM programmes were considered incompatible with competitive retail markets (Molina et al., 2010).

There is a substantial literature on the evaluation of overall DSM programmes. However, the impact of specific financial incentives on adopting energy-efficient appliances has not been studied as extensively. These incentives can be in the form of tax credits or deductions, loan subsidies and cash rebates. Compared to the studies on overall DSM initiatives, the existing literature on the impact of rebate policies on adopting energy-efficient appliances is quite limited and even more so at the aggregated level. At the disaggregated level, the papers by Train and Atherton (1995) and Revelt and Train (1998) are examples of the impact of financial incentives on the choice of efficiency of appliances by residential customers. Revelt and Train (1998) use stated preference data to estimate the impact of rebates and loans on the choice of efficiency of refrigerators and predict that rebates led 8.5% of customers to switch from a standard-efficiency to a high-efficiency refrigerator. Train and Atherton (1995) find that attractive loans with low interest rates or long repayment periods are necessary to have the same effect as rebates and that offering customers the option of loans or rebates are more effective than programmes offering only loans or rebates. Markandya et al. (2009) find that subsidies are, in general, less cost-effective than an energy tax. They conclude that, depending on a particularly country and policy options, it can be cost-effective to promote the use of energy-efficient appliances by using incentives.

Galarraga et al. (2013) analyse the "Renove" programme in Spain and conclude that a tax scheme is a better policy instrument than a subsidy scheme in promoting energy efficiency while advocating a combination of the two to improve the efficiency of energy policy. Davis et al. (2014) analyse a large-scale programme in Mexico that replaces households' old refrigerators and air conditioners with energy-efficient models and find that refrigerator replacement reduces electricity consumption by 8% and air conditioning replacement actually increases electricity consumption. They conclude that the programme is not cost-effective since the cost of reducing $CO_2$ emissions is over US$500 per tonne. Datta and Gulati (2014) use US state-level data and analyse rebates provided to buyers of ENERGY STAR-qualified clothes washers, refrigerators and dishwashers. They find that utility rebates raise the share of ENERGY STAR qualified clothes washers but do not appear to affect dishwasher and refrigerator shares. They estimate the cost for the clothes washers rebate programme to be lower than the estimated cost of building and operating an additional power plant and the average on-peak spot price and conclude that the ENERGY STAR clothes washers rebate programme is, on average, a cost-effective way for utilities to reduce electricity demand. Boomhower and Davis (2014) find that participation in a large-scale residential energy-efficiency programme increases with larger subsidy amounts but that most households would have participated even with much lower subsidy amounts thereby making the large subsidies not cost-effective. Houde and Aldy (2014) evaluate the State Energy Efficient Appliance Rebate Program and estimate the incremental impact of energy efficiency rebates on refrigerators, clothes washers, and dishwashers in the presence of regulatory and information schemes. They estimate the cost-effectiveness to be from US$44 to US$146 per MWh saved and is higher than the average cost-effectiveness for utility-sponsored programmes.

The contribution of this paper is to study the effect of rebate policies on the sales of ENERGY STAR-labelled household appliances using, firstly, a difference-in-differences approach, secondly, a difference-in-differences approach with a potentially endogenous rebate policy variable and, finally, a nonlinear model to account for the low within-variation of some of the explanatory variables. Another contribution is that, compared to the study by Datta and Gulati (2014), we also consider air conditioners in addition to clothes washers, dishwashers, and refrigerators. To apply our methodology we use information from 47 US states between 2001 and 2006 and publicly available data on ENERGY STAR sales shares, coverage of rebate policies and various socio-economic, weather and price variables. The unobserved state-specific heterogeneity in our panel data set-up is controlled by using fixed effects estimation procedures. We also address potential endogeneity issues in the policy variable by using an instrumental variables approach.

The remainder of the paper is organised as follows. In the next section we discuss our empirical specification. We provide a description of the data, its sources and limitations in section 3. The econometric results using the difference-in-differences and instrumental variable approaches are presented in the penultimate section while the final section has concluding remarks.

## 2 Empirical Specification

The policy of utility rebates for ENERGY STAR appliances varies widely across US states and, in many cases, over time within US states. We will use this variation as our identification strategy to measure the impact of the rebates. The policy also differs in terms of the coverage among the customers of utility companies that provide electricity. For example, not all utility companies in a state will offer rebates to its customers. Therefore, the coverage of rebates will vary across states and also within states over time.

We use a panel data set of 47 US states over the period from 2001 to 2006 to estimate the impact of a rebates policy on the share of sales of ENERGY STAR-labelled household appliances. The sales share of ENERGY STAR appliances is assumed to depend on the state-specific rebate policy as well as on various socio-economic characteristics and weather characteristics.

The coverage of these rebates distributed across the US between 2001 and 2006 for four appliances, *viz.*

clothes washers, dishwashers, refrigerators and air conditioners, respectively, is shown in table A1 in the appendix. We find that there is variation both across states and even within states over time. States like Alabama, Arizona and Florida do not have any utility rebates for any appliance over the period of six years while California has utility rebates for at least one appliance type in all years in the same time period. Many states like Colorado, Iowa and Minnesota do not have rebates over the entire period but have some rebates for certain appliances in certain years. We will try to use this variation in rebate policy coverage to capture its impact on the adoption of ENERGY STAR appliances. We will be able to estimate the effect of the rebate policy intervention by using a difference-in-differences (DD) approach. The basic idea behind DD is to identify a policy intervention or treatment and then compare the difference in the outcomes before and after the intervention for the treated groups with the difference for the untreated or control groups. In our case, the treated groups are the states that had the rebate policy in a particular year for a particular appliance while the control groups are the states that had no rebates or states in which the policy was not in effect during a particular year. A typical DD estimation using panel data with more than two time periods will consider individual and year fixed effects. Our DD estimation will, therefore, take into consideration the unobserved time-invariant factors that may influence our dependent variable.

We estimate the model using the following specification:

$$ES_{ait} = \alpha_0 + \alpha_{1a} + \alpha_{2i} + \beta Rebate\ Policy_{it} + \gamma X_{it} + \delta_t + \varepsilon_{it}, \tag{1}$$

where the subscripts $a$, $i$ and $t$ are indices for appliance type, US state, and year, respectively. We have four types of appliances in our data, *viz.*, clothes washers, dishwashers, refrigerators, and air conditioners. $ES_{ait}$ is the share of ENERGY STAR household appliance type $a$ sold, $Rebate\ Policy_{it}$ is the rebate policy variable, $X_{it}$ is a matrix of all other explanatory variables, and $\varepsilon_{it}$ is the idiosyncratic error term.

The appliance type is captured by the $\alpha_{1a}$ terms. Any unobserved state-specific heterogeneity is captured by the $\alpha_{2i}$ terms and the $\delta_t$ terms account for common year-specific fixed effects. Depending on the assumptions we make about the correlation of the $\alpha_i$ terms with the other explanatory variables in eq. (1) we have either a fixed effects model or a random effects model. The advantage of the fixed effects model is that the individual effects may be correlated with the explanatory variables while in the random effects model this correlation is assumed, by definition, to be zero.

Including both time and state-specific fixed effects in eq. (1) enables us to disentangle the impact of the rebates policy from other determinants related to state characteristics or time effects. Our coefficient of interest is $\beta$ which provides us with an estimate of the effect of having a rebate policy on the sales share of

ENERGY STAR appliances. A positive and statistically significant coefficient would suggest that the rebate policies were effective in increasing the share of ENERGY STAR appliances over the period from 2001 to 2006.

Our main independent variable of interest is the rebate policy variable, $\textit{Rebate Policy}_{it}$. If rebate policies have a positive impact on the sale of ENERGY STAR appliances in terms of increasing their sales share as a proportion of all appliances sold, $\beta$ is expected to be positive. However, there may be other factors, given in the matrix $X_{it}$, that may affect the sales share of ENERGY STAR appliances.

The price of residential electricity may influence the share since a higher price of electricity, *ceteris paribus*, may cause households to buy more energy-efficient appliances. The hypothesis is that the higher price of electricity increases the cost of consuming energy and, since energy-efficient appliances have lower consumption costs, households may switch to purchasing more energy-efficient appliances. The impact of rising energy prices, and energy costs in general, on increasing household conservation improvements has been noted by, among others, Pitts and Wittenbach (1981), Walsh (1989), and Long (1993).

An increase in per capita income may have a positive impact on the ENERGY STAR sales share. ENERGY STAR appliances are, on average, more expensive than non-ENERGY STAR appliances. Therefore, if income increases we expect the ENERGY STAR sales share to increase. An increase in income should also lead to an increase in the consumption of electricity. This will increase the cost of consuming electricity and may lead to a switch to a more energy-efficient appliance thus causing the sales of energy-efficient appliances to increase. The higher likelihood of investing in energy-efficient appliances with an increase in income has been noted by, for example, Long (1993), Mills and Schleich (2010), Sardianou and Genoudi (2013), and Ameli and Brandt (2015).

The effect of education may also impact the penetration of ENERGY STAR appliances with more educated people being more aware of ENERGY STAR products. Therefore, we expect an increase in education to increase the sales share of ENERGY STAR appliances. This positive correlation between the level of education and the adoption of energy-efficient technology has been observed by, for example, Mahapatra and Gustavsson (2008), Mills and Schleich (2009), Mills and Schleich (2012), Michelsen and Madlener (2012), and Sardianou and Genoudi (2013).

The sales share of ENERGY STAR appliances may also be affected by the environmental consciousness of households with more environmentally conscious US states having a higher sales share of ENERGY STAR appliances. Studies have shown that environmental preferences may influence the decision to invest in energy-efficient technology (Olli et al., 2001; Kollmuss and Agyeman, 2002; Kahn, 2007; Di Maria et al., 2010; Ameli and Brandt, 2015).

The weather can also have an impact with states experiencing more heating and cooling degree days having higher electricity consumption, thus increasing the cost of consuming energy. More energy-efficient appliances will reduce the cost of consuming energy and, therefore, more heating and cooling degree days are expected to increase the sales share of ENERGY STAR appliances. The effect of weather and climate zones on energy technology adoption has been observed by, for example, Long (1993) and Mills and Schleich (2009).

Certain assumptions need to be met by our model to enable us to identify the impact of the rebates policies. First, we need to exclude the presence of unobserved variables affecting ENERGY STAR sales shares that move systematically over time in a different way between the states. In our analysis, the assumption sounds reasonable because all states are in the US and, therefore, the general trend in ENERGY STAR sales shares is expected to be similar. Moreover, the possibility of unobserved heterogeneity should be negligible given that our regressions include all the main socio-economic determinants of differences in ENERGY STAR sales shares use across the states.

A further assumption is that the decision to have a rebate policy is independent of the ENERGY STAR sales share in a state, i.e. policies are exogenous. However, this assumption may be debatable because it is possible that rebate policies in a state may be driven by the penetration of ENERGY STAR sales share. It is entirely plausible that states with a low ENERGY STAR sales share have rebate policies in place. As noted by Besley and Case (2000), there is a literature in political economy in which state policies may be taken to be endogenous and therefore there is a need to obtain unbiased estimates of the impact of a policy. We therefore seek to improve on our initial results by treating the policy variable as endogenous and using a couple of instrumental variables approaches. An instrumental variable approach will also mitigate any omitted variable bias that may exist.[9] Firstly, we use a standard two stage least squares linear model with instruments in the first stage. Secondly, we use a two stage instrumental variables approach with a probit regression of the endogenous policy variable in the first step and an instrumental variables approach in the second step where the endogenous policy dummy variable is instrumented using the prediction of the policy dummy variable from the probit estimation (Heckman, 1978). We use a political variable as our instrument, namely, the share of Democratic House members in a state. The political variables are missing for the state of Nebraska due to the unusual nature of its legislature. The Nebraska legislature is unicameral and non-partisan and therefore, we do not have any information on the division of the legislature on party lines. We will describe the rationale for considering this instrument in section 4. The remainder of the paper deals with estimating the coefficient $\beta$ in eq. (1).

[9]The panel nature of our data will also mitigate any omitted variable bias arising from omitted variables that exhibit low within-variation.

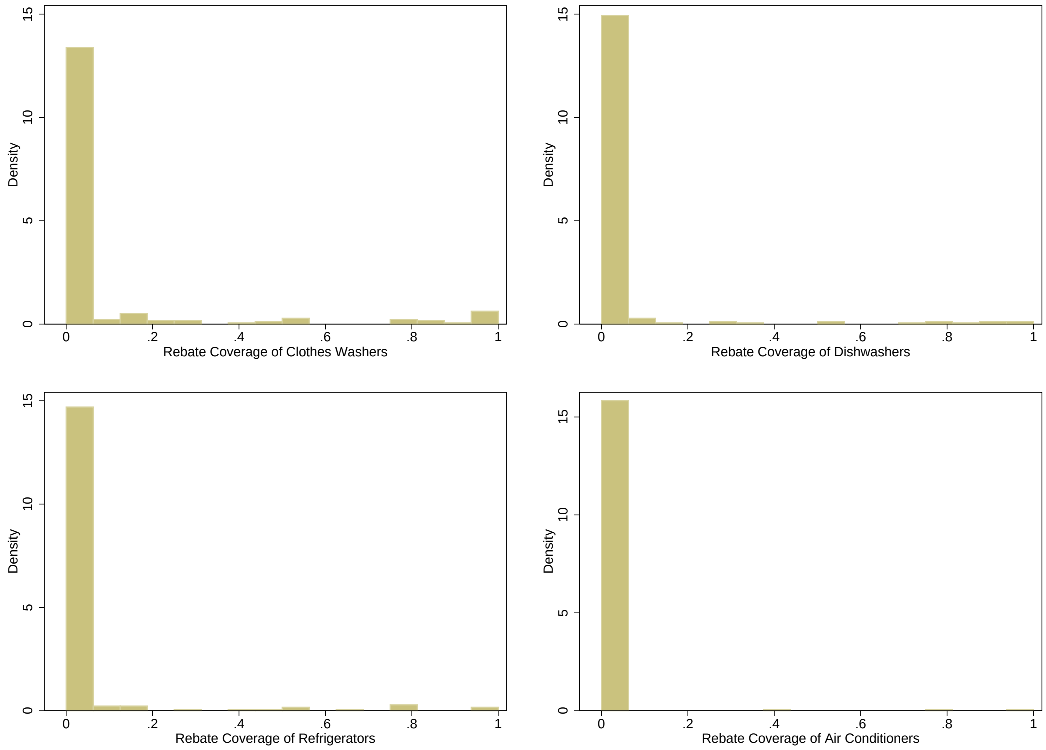


Figure 1: Histogram of rebate policy coverage

As mentioned previously, the coverage of rebates varies within states and also across the four different appliances under consideration, *viz.* clothes washers, dishwashers, refrigerators and air conditioners. Also, rebate policies are not present in all US states. To solve this we use the fraction of people that are covered by rebates. This is calculated by using the number of customers that would be covered under the rebate policy and then using the distribution of the fraction of customers covered to define a cut-off for a policy dummy. It should be noted that the rebate policies under consideration apply only to four major household appliances, *viz.* clothes washers, refrigerators, dishwashers and air conditioners. In many cases, the policies apply to a subset of this group. For example, there could be a rebate for clothes washers and not for the other three appliances. An illustration of the rebate policy coverage is provided in figure 1 while figure 2 illustrates the coverage of rebates for states and years conditional on rebate coverage being greater than zero. Figure 1 shows that there are a lot of observations with no rebates in place during our time period for all the four appliances. Therefore, we also present figure 2 that indicates more variation in the rebate coverage with clothes washers showing a lot more variation than dishwashers and refrigerators while the variation for air conditioners exhibits the least. We will, as mentioned before, use this variation to identify the effect of the rebate coverage on the sales share of ENERGY STAR appliances.

We consider a coverage of 11.4%, the median, as our critical value. Therefore, in our framework, a state is considered to have a value of one for the rebate policy variable if the coverage of the rebates exceeds the

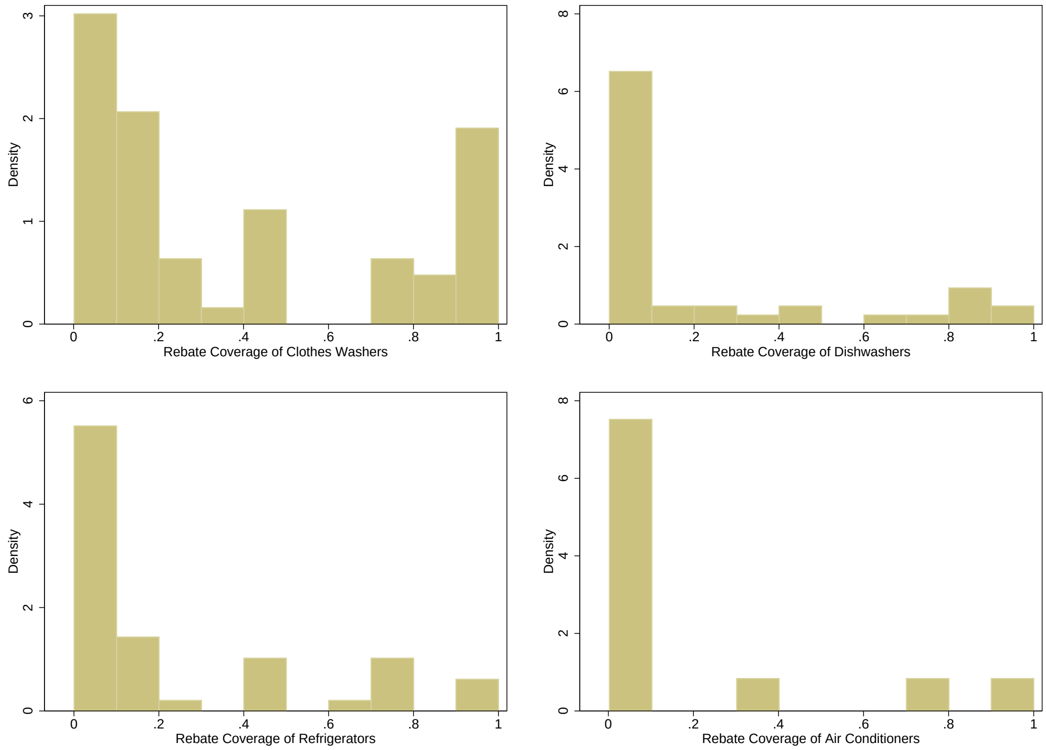


Figure 2: Histogram of rebate policy coverage, conditional on rebate policy coverage greater than zero

cut-off value. In all our subsequent discussions, states that are less than the 11.4% coverage are categorized as those states with no rebate policies while those with a coverage of greater than or equal to 11.4% are considered states that have rebate policies. We have used a binary policy dummy due to the wide variation in rebate policies that could lead to measurement error. We also consider a range of rebate coverage values to check for the robustness of our main results. To do this, we vary the cut-off value starting with rebate coverage strictly greater than zero, rebate coverage at the first quartile and, finally, rebate coverage at the third quartile. It should be noted that the cut-off values for the first quartile, median, and third quartile are calculated conditionally based on rebate coverage being greater than zero. The results are described in section 4.

# 3 Data Description

Annual data of US states between 2001 and 2006 have been compiled from a number of sources. We restrict our analysis to almost all of the contiguous US states and exclude the District of Columbia and the states of Alaska and Hawaii from our analysis. The state of Rhode Island is excluded due to incomplete information. The sales shares of ENERGY STAR appliances are from the US Department of Energy (DOE). The price of residential electricity is from the Energy Information Administration (EIA) of the US Department of Energy.

The price of residential electricity is an average price calculated by the EIA from dividing the revenue of the utility companies coming from the residential sector with the volume of electricity sales to the residential sector.[10]

The ENERGY STAR website has data on sales of the four major appliances, *viz.* clothes washers, dishwashers, air conditioners and refrigerators.[11] The annual data are disaggregated by the type of major appliance in each US state. Sales of the four appliances are categorised into ENERGY STAR and non-ENERGY STAR units. The appliance manufacturers report the sale of ENERGY STAR units to the EPA every year. The EPA uses the difference of the sales figures of total ENERGY STAR units sold and the total US sales obtained from industry reports to obtain sales figures of non-ENERGY STAR units.

The socio-economic data used in our models are obtained from the Bureau of Economic Analysis of the US Census Bureau. The variables include population, per capita income, and percentage of people who are at least high school graduates. The nominal values of the relevant variables are converted to real values by dividing them with the consumer price index obtained from the U.S. Bureau of Labor Statistics (2010), so the price of electricity and per capita income are all in real terms. Information on heating and cooling degree days (HDD and CDD, respectively) is from the National Climatic Data Center at the National Oceanic and Atmospheric Administration (NOAA). There may be an aggregation issue as the HDD and CDD are for the entire state. However, since our sales data are at the state level we need to use the state average for HDD and CDD. According to various reports of the Historical Climatology Series from NOAA, "the state average degree day totals for each month are derived from the divisional values by weighting each division by its percentage of the total state population as adduced from the 2000 census data (Bureau of Census, 2002). The population weighting procedure assures that degree-day averages for the states as a whole are biased toward conditions existing in the more populous sections of the states." The penetration of ENERGY STAR appliances may also depend on the environmental consciousness of a state's population. To control for this we use the percentage of a state's population who are members of the Sierra Club, an environmental organization in the US.[12] The number of Sierra Club members in each US state has been obtained directly from the Sierra Club upon request. We also use an instrumental variable to solve for potential endogeneity issues in the regression. The instrument is the fraction of House members in a state who belong to the Democratic party. Data on the House members is from the US Census Bureau.[13] Summary statistics of all the variables are presented in Table 1.

[10] The information on revenue and sales of individual utility companies are reported annually to the EIA in form 861.

[11] ENERGY STAR website, accessed 24 July, 2008

[12] "[...] America's largest and most influential grassroots environmental organization", `http://www.sierraclub.org/`, website accessed 25 April 2012.

[13] `http://www.census.gov/compendia/statab/cats/elections/gubernatorial_and_state_legislatures.html`, website accessed 30 September, 2011.

Table 1: Summary Statistics

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| ENERGY STAR share | 0.370 | 0.230 | 0.033 | 0.990 | 1128 |
| Rebate Policy | 0.074 | 0.263 | 0 | 1 | 1128 |
| Log Price of Electricity | -3.091 | 0.221 | -3.480 | -2.479 | 1128 |
| Log Per Capita Income | 9.627 | 0.127 | 9.365 | 9.968 | 1128 |
| Percentage of High School Graduates | 86.101 | 3.793 | 77.2 | 93 | 1128 |
| Log Cooling Degree Days | 6.816 | 0.708 | 5.112 | 8.207 | 1128 |
| Log Heating Degree Days | 8.422 | 0.508 | 6.404 | 9.138 | 1128 |
| Percentage of Sierra Club members | 0.238 | 0.143 | 0.036 | 0.673 | 1128 |
| Fraction of Democratic House members | 0.498 | 0.144 | 0.130 | 0.880 | 1104 |

The rebate policy variable, $Rebate\ Policy_{it}$, is binary and constructed using data about rebates obtained from D&R International Ltd. It is assigned a value of one when a state has a rebate programme in place in a year for a particular appliance type that covers more than 11.4% of the population while it is zero otherwise. Table 2 provides an overview of all the US states for clothes washers, dishwashers, refrigerators and air conditioners, respectively, we have considered and their corresponding rebate policies between 2001 and 2006. States which had rebates offered by any utility company in a particular year are marked with a "■" in the table. The tables indicate a lot of variation for clothes washers and refrigerators compared to dishwashers and, especially, air conditioners. The mean values of the rebate coverage are presented in table A1 in the appendix. Table A1 indicates a lot of variation for clothes washers, refrigerators and dishwashers rebate coverage compared to air conditioners.

Table 2: Implementation of rebate policies in the US by state and year for clothes washers (CW), dishwashers (DW), refrigerators (RF) and air conditioners (AC)

| | 2001 | | | | 2002 | | | | 2003 | | | | 2004 | | | | 2005 | | | | 2006 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **State** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** |
| AL | | | | | | | | | | | | | | | | | | | | | | | | |
| AZ | | | | | | | | | | | | | | | | | | | | | | | | |
| AR | | | | | | | | | | | | | | | | | | | | | | | | |
| CA | | | | | ■ | | | | ■ | | | | | ■ | ■ | ■ | | ■ | ■ | ■ | | ■ | ■ | ■ |
| CO | | | | | | | | | | | | | | | | | | | | | | ■ | | |
| CT | | | | | | | | | ■ | | ■ | ■ | ■ | | | | | ■ | | | ■ | ■ | | ■ |
| DE | | | | | | | | | | | | | | | | | | | | | | ■ | | ■ |
| FL | | | | | | | | | | | | | | | | | | | | | | | | |
| GA | | | | | | | | | | | | | | | | | | | | | | | | |
| ID | | | | | | | | | | | | | | | | | | | | | | | | |
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| IN | | | | | | | | | | | | | | | | | | | | | | | | |
| IO | | | | | | | | | | | | | | | | | | | | | | | | |
| KS | | | | | | | | | | | | | | | | | | | | | | | | |
| KT | | | | | | | | | | | | | | | | | | | | | | | | |
| LO | | | | | | | | | | | | | | | | | | | | | | | | |
| ME | | | | | | | | | | | | | | | | | | | | | | | | |
| MD | | | | | | | | | | | | | | | | | | | | | | | | |
| MA | | | | | | | | | ■ | | | | | ■ | | | | ■ | | | | ■ | | |
| MI | | | | | | | | | | | | | | | | | | | | | | | | |
| MN | | | | | | | | | | | ■ | | | ■ | | | | ■ | ■ | ■ | | ■ | ■ | ■ |
| MS | | | | | | | | | | | | | | | | | | | | | | | | |
| MO | | | | | | | | | | | | | | | | | | | | | | | | |
| MT | | | | | | | | | ■ | | | | | | | | | | | | | ■ | | |
| NE | | | | | | | | | | | | | | | | | | | | | | | | |
| NV | | | | | | | | | ■ | ■ | | | | ■ | ■ | ■ | | ■ | | ■ | | ■ | | ■ |
| NH | | | | | ■ | | | | ■ | | | | | ■ | | | | ■ | | | | ■ | | |
| NJ | | | | | | | | | | | | | | | | | | | | | | | | |

Continued on next page

Table 2 – continued from previous page

| **State** | **2001 CW** | **2001 DW** | **2001 RF** | **2001 AC** | **2002 CW** | **2002 DW** | **2002 RF** | **2002 AC** | **2003 CW** | **2003 DW** | **2003 RF** | **2003 AC** | **2004 CW** | **2004 DW** | **2004 RF** | **2004 AC** | **2005 CW** | **2005 DW** | **2005 RF** | **2005 AC** | **2006 CW** | **2006 DW** | **2006 RF** | **2006 AC** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| NM | | | | | | | | | | | | | | | | | | | | | | | | |
| NY | | | | | | | | | | | | | | | | | | ■ | | | | ■ | | |
| NC | | | | | | | | | | | | | | | | | | | | | | | | |
| ND | | | | | | | | | | | | | | | | | | | | | | | | |
| OH | | | | | | | | | | | | | | | | | | | | | | | | |
| OK | | | | | | | | | | | | | | | | | | | | | | | | |
| OR | | | | | | | | | ■ | ■ | ■ | | | ■ | ■ | | | ■ | ■ | | | ■ | ■ | ■ |
| PA | | | | | | | | | | | | | | | | | | | | | | | | |
| SC | | | | | | | | | | | | | | | | | | | | | | | | |
| SD | | | | | | | | | | | | | | | | | | | | | | | | |
| TN | | | | | | | | | | | | | | | | | | | | | | | | |
| TX | | | | | | | | | | | | | | | | | | | | | | | | |
| UT | | | | | | | | | | | | | | | | | | | | | | | | |
| VT | | | | | | | | | | | ■ | | | ■ | | ■ | | ■ | | ■ | | ■ | | ■ |
| VA | | | | | | | | | | | | | | | | | | | | | | | | |
| WA | | | | | ■ | | | | ■ | ■ | | | | ■ | ■ | ■ | | ■ | ■ | ■ | | ■ | ■ | ■ |
| WV | | | | | | | | | | | | | | | | | | | | | | | | |
| WI | | | | | | | | | | | | | | ■ | | | | | | | | | | ■ |
| WY | | | | | | | | | | | | | | | | | | | | | | | | |

*Note:* States with rebate policy coverage ≥ 0.114 in Table A1 denoted by ■

## 4 Estimation and Results

We now describe the methods used to estimate eq.(1) and present the results. The dependent variable in all our specifications is the sales share of ENERGY STAR appliances. There are several approaches to estimating the equation which include the pooled ordinary least squares model (POLS), the random effects model (RE) and the fixed effects model (FE). Our objective is to estimate the effect of the rebate policies using a DD framework and we employ a standard test to choose the most appropriate method to estimate the effect of the policy variable. Since our primary identification strategy uses a difference-in-differences framework we focus our attention on the POLS and FE models.

We perform an $F$-test to indicate that the POLS model can be rejected in favour of panel data methods of estimation. The null hypothesis of the $F$-test is that the constant terms are equal across all the states and this is rejected. This means that there are significant state-level effects and the POLS model is inappropriate when compared to the FE model.[14] Therefore, for our subsequent analyses, we only consider a DD estimator with state fixed effects. The results from estimating eq. (1) using fixed effects are presented in column FE1. The coefficient of *Rebate Policy* is positive and significant. The rebate policy appears to increase the share of ENERGY STAR appliances by about 3.3 percentage points. This translates to an increase in the share of ENERGY STAR appliances of about 9% at the mean share.

However, as discussed previously, a potential problem with the previous estimation method is the possible endogeneity of $Rebate\ Policy_{it}$ in eq. (1). This may be due to simultaneous causality that could run from the adoption of ENERGY STAR appliances to the rebate policy. It may be that the rebate policies are influenced by the penetration of ENERGY STAR appliances. We try to solve this problem by considering two instrumental variable approaches. In the first approach we use the standard approach and predict the policy dummy variable in the first stage by using a linear probability model. The results from an instrumental variable two-stage least squares model (2SLS) are presented in column FE2. The coefficient for *Rebate Policy* is positive but not statistically significant.

The presence of a possible endogenous binary policy variable indicates a situation described in Heckman (1978). Therefore, in the second approach with an instrumental variable, we use a probit model to model the nonlinear binary policy variable. The instrumental variable is used in this probit stage along with the other explanatory variables. We then use the prediction of the policy variable from this stage as an instrument for the endogenous binary policy variable in a fixed effects instrumental variables regression model. This is a consistent estimation method proposed by Amemiya (1978), Heckman (1978) and Lee (1979).[15] The

[14] The $F$-statistic for this test is 197.65 which easily exceeds the critical value of 2.32 for the $F_{10,1071}$-distribution at the 1% level of significance.

[15] Wooldridge (2002, p. 939) provides a description of this method.

instrumental variable is the excluded instrument in this model. Including the prediction from the probit stage in the latter model as an explanatory variable and not as an instrument will lead to a "forbidden regression" (Angrist and Pischke, 2008).

An instrument should satisfy the conditions for relevance and exogeneity. It should, therefore, be correlated with the rebate policy variable but not with the error term. The instrument we have chosen is the fraction of Democratic members in the House of each US state. The rationale is that we expect the composition of the legislature to be correlated with the rebate policy in a state but uncorrelated with the adoption of energy-efficient appliances by residential households. The suitability of the instrument using a statistical measure can be gauged by inspecting the $F$-statistic of the first stage with a high value, typically over 10, indicating that the instrument does not suffer from a problem of weak instrument.[16] Using the procedure described by Wooldridge (2002) we perform another instrumental variables estimation which exploits the binary nature of our policy variable by first fitting a nonlinear model, a probit in our case. This is done by fitting a probit model of the rebate policy variable using the fraction of Democratic House members as an instrument and all the other exogenous variables by maximum likelihood. We then obtain the fitted probabilities of the response variable and use these values as instruments and other explanatory variables to estimate eq. (1).

The effects of rebate policies on ENERGY STAR sales share are reported in table 3. All the regression results include state-level fixed effects and year fixed effects. The state-level fixed effects will capture any unobserved heterogeneity while the year fixed effects will capture any common time shocks faced by the US states. The results are stable and no structural differences are observed across the models.

Given our empirical specification, we can make predictions with regard to the expected sign of the coefficients. Some of the socio-demographic variables in the specification affect the dependent variable, the sales of ENERGY STAR appliances, through their impact on electricity consumption. The price of electricity, household size and degree days are negatively correlated with the consumption of electricity because an increase in each of these variables will increase the cost of consuming electricity and therefore, should increase the sale of energy-efficient appliances. The expected sign of these coefficients should be positive. An increase in income should increase the cost of consuming electricity because more electricity will be consumed and this should increase the sales of energy-efficient appliances. Also, ENERGY STAR appliances are typically more expensive than equivalent appliances and an increase in income could also increase the sale of ENERGY STAR appliances. The coefficient should, therefore, be positive. The effects of

[16] We have also performed a regression by including the "Fraction of Democratic House members" as an explanatory variable in eq.(1) and the estimated coefficient is not statistically significant even at the 10% level of significance. This also indicates that the variable is appropriate as an instrument since it does not influence our dependent variable directly.

Table 3: Fixed Effects Models of ENERGY STAR share

| | FE1 | FE2 | FE3 |
|---|---|---|---|
| Rebate Policy | 0.033$^b$ | 0.107 | 0.066$^b$ |
| | (0.017) | (0.124) | (0.031) |
| Log Price of Electricity | -0.006 | -0.035 | -0.020 |
| | (0.087) | (0.100) | (0.087) |
| Log Per Capita Income | 0.101 | 0.099 | 0.102 |
| | (0.169) | (0.170) | (0.168) |
| Percentage of High School Graduates | 0.003 | 0.004 | 0.003 |
| | (0.004) | (0.004) | (0.004) |
| Log Cooling Degree Days | -0.024 | -0.039 | -0.031 |
| | (0.028) | (0.038) | (0.028) |
| Log Heating Degree Days | -0.096 | -0.098 | -0.099 |
| | (0.102) | (0.102) | (0.101) |
| Percentage of Sierra Club members | 0.102 | 0.093 | 0.091 |
| | (0.196) | (0.208) | (0.195) |
| Appliance fixed effects | Yes | Yes | Yes |
| State fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,128 | 1,104 | 1,128 |
| Adjusted $R^2$ | 0.748 | | |
| First Stage $F$-statistic | | 19.150 | 436.899 |

Standard errors in parentheses.
$^a$, $^b$, $^c$: Significant at the 1%, 5% and 10% levels, respectively.

schooling, as measured by the percentage of high school graduates, and the environmental consciousness of the population in general, as measured by the percentage of membership in the Sierra Club, an environmental organization, are also expected to be positive on the sales of energy-efficient appliances.

In all the fixed effects models the relatively low number of statistically significant coefficients of socioeconomic variables can be explained, as suggested by Cameron and Trivedi (2005), by the low within variation of these variables. The number of significant coefficients increases in the instrumental variables model, FE3. However our main goal in this paper is to estimate the coefficient of the rebate policy dummy variable using a DD framework. The coefficient for *Rebate Policy* in model FE2 is higher than the difference-in-differences estimation of the model, FE1, but is not statistically significant. However, the estimate of *Rebate Policy* in FE3 using the Heckman-type estimator is positive, significantly different from zero and larger in magnitude than both the estimates in FE1 and FE2. The advantage of using FE3 is that the standard errors are smaller and we can obtain a more precise estimate. Another advantage is that the probit model in the first stage does not need to be correctly specified (Wooldridge, 2002). Due to these reasons, FE3 is our preferred specification over FE2. The first stage regression in FE2 indicates that, with a high value of $F$-statistic, the fraction of Democratic House members does not suffer from a problem of being a weak instrument. The first stage

Table 4: First Stage of IV/2SLS Estimation

| | FE2 | FE3 |
|---|---|---|
| Log Price of Electricity | 0.366[b] | 0.153 |
| | (0.161) | (0.135) |
| Log Per Capita Income | 0.036 | -0.072 |
| | (0.314) | (0.262) |
| Percentage of High School Graduates | -0.008 | -0.009 |
| | (0.007) | (0.006) |
| Log Cooling Degree Days | 0.213[a] | 0.044 |
| | (0.051) | (0.044) |
| Log Heating Degree Days | 0.021 | -0.132 |
| | (0.189) | (0.158) |
| Percentage of Sierra Club members | 0.318 | -0.154 |
| | (0.377) | (0.305) |
| Fraction of Democratic House members[d] | 0.783[a] | |
| | (0.179) | |
| Probability(Rebate Policy)[e] | | 0.993[a] |
| | | (0.048) |
| Observations | 1,104 | 1,128 |

Standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.
[d] Used in the probit stage of IV/FE3.
[e] Estimated in the probit stage.

of FE3 that uses the predicted probability of the binary policy variable as an instrument for the endogenous variable indicates a very high $F$-statistic.

As explained previously, the control group consists of all the states that do not have a sufficiently large coverage of a rebates policy in a year to increase ENERGY STAR household appliances share between 2001 and 2006. Thus, when we study the effects of the rebate policies, the controls are the states that either do not have a policy in a year or the coverage is less than 11.4% of the customers. The estimated coefficient of *Rebate Policy* measures the impact of the policy. In line with our expectations, policy coefficients are significant in all the models apart from FE2. The binary policy variable has a positive sign, which suggests that the implementation of rebates leads to an increase in the sales of ENERGY STAR appliances. The estimated coefficient of *Rebate Policy* in FE1 indicates that rebates may increase the sales share of ENERGY STAR appliances by around 3.3 percentage points. This roughly represents an impact of around 9% on the mean level of ENERGY STAR sales share in US states between 2001 and 2006. Using the estimated coefficient of *Rebate Policy* in FE3, we observe that adopting rebates may increase the sales share of ENERGY STAR appliances by around 6.6 percentage points. This roughly represents an impact of around 18% on the mean level of ENERGY STAR sales share in US states between 2001 and 2006.

To check the robustness of our results we perform some more estimations by varying the cut-off for defining the rebate policy binary variable. The results of these models are reported in the appendix. We have, in our estimations reported in table 3, used the median of the rebate coverage as the cut-off. We vary the cut-off for the rebate policy binary variable in three other ways. First, the binary variable is defined as having a value of one if the rebate coverage is greater than zero and zero, otherwise. The results of this robustness check are provided in table A2. The coefficient for the FE1 model, the basic difference-in-differences model, is the same in table A2 as it is in table 3. The coefficients for the models using instrumental variables, FE2 and FE3, are slightly higher in table A3. Second, the binary variable is defined as having a value of one if the rebate coverage is greater than the value of the first quartile of the rebate coverage and zero, otherwise. The results are provided in table A4. The coefficient for the FE1 model, the basic difference-in-differences model, is almost the same as it is in table 3. The coefficients for the models using instrumental variables, FE2 and FE3, are different in table A5 with the estimate lower in FE2 and higher in FE3 compared to the estimates in table 3. Third, the binary variable is defined as having a value of one if the rebate coverage is greater than the value of the third quartile of the rebate coverage and zero, otherwise. The results of these regression models are provided in table A6. The estimates are very similar for FE1 and FE3 but higher for FE2 when compared to the corresponding models in table 3. However, the estimated coefficients for *Rebate Policy* in all cases are not statistically significant. The first stage regressions in the FE2 models for all our robustness checks indicate that, with a high value of $F$-statistic, the fraction of Democratic House members does not suffer from a problem of being a weak instrument. The first stages of FE3 that uses the predicted probability of the binary policy variable as an instrument for the endogenous variable also indicate a very high $F$-statistic consistently over all the robustness specifications.

Our results and the robustness checks indicate that the difference-in-differences results appear to be very stable across all the specifications with the rebate policy coverage having an impact of around 3 percentage points on the sales share of ENERGY STAR appliances. However, the results for the instrumental variable models using a nonlinear approach indicate that the impact is higher and exhibits more variability with the estimates of the effect ranging from around 7 to around 10 percentage points.

# 5 Conclusion

In this paper we estimate the impact of rebate policies in the US on the sales share of energy-efficient ENERGY STAR household appliances by using a difference-in-differences approach as well as a nonlinear model. We use the coverage of rebate policies as a measure of the rebate policies. The difference-in-differences approach allows us to identify the effect of rebate policies by correlating differential changes in the sales of ENERGY STAR appliances across US states and over time to changes in the rebate policy variable while the nonlinear model exploits the binary nature of the potentially endogenous policy variable. The policy variable may be endogenous due to potential simultaneity and omitted variable biases. We find that the estimated impact of the rebate policies on the sales share of ENERGY STAR appliances ranges from 3.3 percentage points, when using a difference-in-differences approach, to 6.6 percentage points, when using a nonlinear model. The results are higher than the findings in Datta and Gulati (2014) who find that, on average, rebates increase the sales of ENERGY STAR clothes washers by 6%. Our estimates, based on the average sales share of ENERGY STAR appliances, indicate an increase in the sales share of between 9% and 18%.

The main contribution of this paper is to use an instrumental variable approach to solve for the possible endogeneity of rebate policies. Using this approach, our results show that the use of rebates appear to be an effective tool to increase the uptake of certain ENERGY STAR household appliances. However, there are some possible limitations of this study. The effectiveness of programmes for promoting energy-efficient appliances depends on the electricity usage after the uptake. There is the possibility of a rebound effect, both direct and indirect, that we are unable to account for. However, Davis (2008) estimates the direct rebound effect to be very low for clothes washers. There is also the possibility of free-riders who would have purchased an ENERGY STAR appliance even in the absence of the rebate programmes. For example, Boomhower and Davis (2014) estimate that around half of the participants in a residential energy efficiency programme are free-riders. The presence of the rebound effect and free-riders will diminish the effectiveness of subsidies for energy-efficient appliances.

In spite of these limitations, our results suggest that providing subsidies may increase the uptake of more energy-efficient ENERGY STAR appliances. There are not many studies that have estimated the impact of providing state-wide rebates on the sales of ENERGY STAR household appliances. It is, therefore, important to analyse such policies, especially at a more disaggregated level of sales, to have a good understanding of the impact of subsidies and provide policy makers with recommendations on various approaches to increase the uptake of more energy-efficient appliances.

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# Appendix

Table A1: Coverage of rebate policies in the US by state and year for clothes washers (CW), dishwashers (DW), refrigerators (RF) and air conditioners (AC)

| | 2001 | | | | 2002 | | | | 2003 | | | | 2004 | | | | 2005 | | | | 2006 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **State** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** | **CW** | **DW** | **RF** | **AC** |
| AL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| AZ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| AR | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CA | 0.098 | 0 | 0.001 | 0 | 0.155 | 0 | 0.001 | 0 | 0.188 | 0.007 | 0.015 | 0 | 0.912 | 0.882 | 0.427 | 0 | 1 | 1 | 0.442 | 0.003 | 1 | 1 | 1 | 0.008 |
| CO | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.014 | 0 | 0 | 0 | 0.037 | 0.001 | 0.001 | 0 | 0.038 | 0.002 | 0.002 | 0 | 0.122 | 0.002 | 0.030 | 0 |
| CT | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.758 | 0.5 | 0 | 0.758 | 0.379 |
| DE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 |
| FL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| GA | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ID | 0 | 0 | 0 | 0 | 0.019 | 0.019 | 0 | 0 | 0.032 | 0.027 | 0 | 0 | 0.054 | 0.028 | 0.001 | 0 | 0.002 | 0.002 | 0.002 | 0 | 0.029 | 0.037 | 0.020 | 0 |
| IL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.149 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| IN | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| IO | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.004 | 0.007 | 0.004 | 0 | 0 | 0.003 | 0 | 0 | 0.066 | 0.066 | 0.028 | 0 |
| KS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| KY | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| LO | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ME | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MA | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.144 | 0.026 | 0 | 0 | 0.439 | 0.026 | 0 | 0 | 0.828 | 0 | 0 | 0 | 0.820 | 0 | 0 | 0 |
| MI | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MN | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.114 | 0 | 0.270 | 0 | 0 | 0 | 0.122 | 0.122 | 0.122 | 0 | 0.174 | 0.146 | 0.146 | 0.033 |
| MS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MO | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MT | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.234 | 0 | 0 | 0 | 0.007 | 0.007 | 0.007 | 0 | 0.015 | 0.015 | 0.015 | 0 | 0.130 | 0.083 | 0.083 | 0 |
| NE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| NV | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.750 | 0.500 | 0 | 0 | 0.500 | 0.500 | 0.500 | 0 | 0.750 | 0 | 0.750 | 0 | 0.750 | 0 | 0.750 | 0 |
| NH | 0 | 0 | 0 | 0 | 0.297 | 0 | 0 | 0 | 0.397 | 0 | 0 | 0 | 0.500 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.5 | 0 | 0 | 0 |
| NJ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| NM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| NY | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.145 | 0 | 0 | 0 | 0.145 | 0 | 0 | 0 |
| NC | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ND | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| OH | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| OK | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| OR | 0.005 | 0.005 | 0.005 | 0 | 0.061 | 0.099 | 0.021 | 0 | 0.290 | 0.318 | 0.122 | 0 | 0.491 | 0.282 | 0.051 | 0 | 0.200 | 0.257 | 0.052 | 0 | 0.865 | 0.803 | 0.643 | 0 |
| PA | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| SC | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| SD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.007 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| TN | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| TX | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| UT | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| VT | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.500 | 0 | 1 | 0 | 0.750 | 0 | 1 | 0 | 0.750 | 0 | 0.750 | 0 | 1 | 0 |
| VA | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| WA | 0.009 | 0.003 | 0.003 | 0.003 | 0.163 | 0.070 | 0.025 | 0.007 | 0.941 | 0.756 | 0.039 | 0.007 | 0.998 | 0.692 | 0.137 | 0.007 | 1 | 0.830 | 0.172 | 0.007 | 1 | 0.876 | 0.296 | 0.007 |
| WV | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| WI | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.165 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.166 | 0 |
| WY | 0 | 0 | 0 | 0 | 0 | 0.010 | 0.010 | 0 | 0 | 0.019 | 0.019 | 0 | 0 | 0.019 | 0.019 | 0 | 0 | 0.019 | 0.019 | 0 | 0.019 | 0.019 | 0.019 | 0 |

Table A2: Fixed Effects Models of ENERGY STAR share

| | FE1 | FE2 | FE3 |
|---|---|---|---|
| Rebate Policy | 0.033[b] | 0.060 | 0.116[a] |
| | (0.014) | (0.068) | (0.036) |
| Log Price of Electricity | -0.007 | -0.018 | -0.042 |
| | (0.087) | (0.091) | (0.089) |
| Log Per Capita Income | 0.077 | 0.053 | 0.022 |
| | (0.169) | (0.175) | (0.172) |
| Percentage of High School Graduates | 0.003 | 0.003 | 0.003 |
| | (0.004) | (0.004) | (0.004) |
| Log Cooling Degree Days | -0.013 | -0.008 | -0.001 |
| | (0.028) | (0.029) | (0.028) |
| Log Heating Degree Days | -0.095 | -0.092 | -0.098 |
| | (0.101) | (0.101) | (0.102) |
| Percentage of Sierra Club members | 0.119 | 0.142 | 0.134 |
| | (0.196) | (0.203) | (0.197) |
| Appliance fixed effects | Yes | Yes | Yes |
| State fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,128 | 1,104 | 1,128 |
| Adjusted $R^2$ | 0.748 | | |
| First Stage $F$-statistic | | 46.695 | 209.065 |

Standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

Table A3: First Stage of IV/2SLS Estimation

| | FE2 | FE3 |
|---|---|---|
| Log Price of Electricity | 0.369[b] | 0.572[a] |
| | (0.185) | (0.171) |
| Log Per Capita Income | 0.831[b] | 0.097 |
| | (0.361) | (0.333) |
| Percentage of High School Graduates | -0.001 | -0.003 |
| | (0.009) | (0.008) |
| Log Cooling Degree Days | -0.145[b] | -0.001 |
| | (0.059) | (0.055) |
| Log Heating Degree Days | -0.065 | 0.058 |
| | (0.217) | (0.199) |
| Percentage of Sierra Club members | -0.250 | -1.115[a] |
| | (0.433) | (0.390) |
| Fraction of Democratic House members[d] | 1.404[a] | |
| | (0.205) | |
| Probability(Rebate Policy)[e] | | 1.013[a] |
| | | (0.070) |
| Observations | 1,104 | 1,128 |

Standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.
[d] Used in the probit stage of IV/FE3.
[e] Estimated in the probit stage.

Table A4: Fixed Effects Models of ENERGY STAR share

| | FE1 | FE2 | FE3 |
|---|---|---|---|
| Rebate Policy | $0.029^b$ | 0.067 | $0.101^a$ |
| | (0.014) | (0.076) | (0.030) |
| Log Price of Electricity | -0.005 | -0.019 | -0.033 |
| | (0.087) | (0.092) | (0.088) |
| Log Per Capita Income | 0.080 | 0.049 | 0.031 |
| | (0.169) | (0.177) | (0.171) |
| Percentage of High School Graduates | 0.003 | 0.003 | 0.003 |
| | (0.004) | (0.004) | (0.004) |
| Log Cooling Degree Days | -0.022 | -0.026 | -0.033 |
| | (0.028) | (0.030) | (0.028) |
| Log Heating Degree Days | -0.094 | -0.092 | -0.096 |
| | (0.102) | (0.101) | (0.102) |
| Percentage of Sierra Club members | 0.104 | 0.108 | 0.081 |
| | (0.196) | (0.204) | (0.197) |
| Appliance fixed effects | Yes | Yes | Yes |
| State fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,128 | 1,104 | 1,128 |
| Adjusted $R^2$ | 0.748 | | |
| First Stage $F$-statistic | | 37.512 | 310.508 |

Standard errors in parentheses.
$^a$, $^b$, $^c$: Significant at the 1%, 5% and 10% levels, respectively.

Table A5: First Stage of IV/2SLS Estimation

| | FE2 | FE3 |
|---|---|---|
| Log Price of Electricity | $0.348^c$ | $0.334^b$ |
| | (0.185) | (0.164) |
| Log Per Capita Income | $0.810^b$ | 0.460 |
| | (0.361) | (0.318) |
| Percentage of High School Graduates | -0.006 | -0.008 |
| | (0.009) | (0.008) |
| Log Cooling Degree Days | $0.150^b$ | $0.103^b$ |
| | (0.059) | (0.052) |
| Log Heating Degree Days | -0.060 | -0.011 |
| | (0.217) | (0.191) |
| Percentage of Sierra Club members | 0.295 | $-0.814^b$ |
| | (0.433) | (0.374) |
| Fraction of Democratic House members$^d$ | $1.260^a$ | |
| | (0.206) | |
| Probability(Rebate Policy)$^e$ | | $1.085^a$ |
| | | (0.062) |
| Observations | 1,104 | 1,128 |

Standard errors in parentheses.
$^a$, $^b$, $^c$: Significant at the 1%, 5% and 10% levels, respectively.
$^d$ Used in the probit stage of IV/FE3.
$^e$ Estimated in the probit stage.

Table A6: Fixed Effects Models of ENERGY STAR share

| | FE1 | FE2 | FE3 |
|---|---|---|---|
| Rebate Policy | 0.027 | 0.161 | 0.075 |
| | (0.020) | (0.188) | (0.051) |
| Log Price of Electricity | -0.001 | -0.040 | -0.039 |
| | (0.087) | (0.104) | (0.100) |
| Log Per Capita Income | 0.095 | 0.068 | 0.124 |
| | (0.169) | (0.175) | (0.182) |
| Percentage of High School Graduates | 0.003 | 0.003 | 0.003 |
| | (0.004) | (0.004) | (0.004) |
| Log Cooling Degree Days | -0.021 | -0.036 | -0.023 |
| | (0.028) | (0.036) | (0.028) |
| Log Heating Degree Days | -0.102 | -0.138 | -0.163 |
| | (0.102) | (0.117) | (0.109) |
| Percentage of Sierra Club members | 0.123 | 0.196 | 0.121 |
| | (0.196) | (0.221) | (0.194) |
| Appliance fixed effects | Yes | Yes | Yes |
| State fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,128 | 1,104 | 940 |
| Adjusted $R^2$ | 0.747 | | |
| First Stage $F$-statistic | | 12.686 | 160.604 |

Standard errors in parentheses.
$^a$, $^b$, $^c$: Significant at the 1%, 5% and 10% levels, respectively.

Table A7: First Stage of IV/2SLS Estimation

| | FE2 | FE3 |
|---|---|---|
| Log Price of Electricity | $0.274^b$ | 0.166 |
| | (0.132) | (0.152) |
| Log Per Capita Income | 0.215 | -0.192 |
| | (0.257) | (0.282) |
| Percentage of High School Graduates | -0.003 | -0.002 |
| | (0.006) | (0.007) |
| Log Cooling Degree Days | $0.123^a$ | -0.018 |
| | (0.042) | (0.043) |
| Log Heating Degree Days | $0.262^c$ | 0.134 |
| | (0.154) | (0.168) |
| Percentage of Sierra Club members | -0.425 | -0.272 |
| | (0.308) | (0.301) |
| Fraction of Democratic House members$^d$ | $0.521^a$ | |
| | (0.146) | |
| Probability(Rebate Policy)$^e$ | | $0.983^a$ |
| | | (0.078) |
| Observations | 1,104 | 940 |

Standard errors in parentheses.
$^a$, $^b$, $^c$: Significant at the 1%, 5% and 10% levels, respectively.
$^d$ Used in the probit stage of IV/FE3.
$^e$ Estimated in the probit stage.